An Efficient Wireless Resource Allocation Based on a Data Compressor Predictor

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Abstract. This paper discussed the resource allocation and reservation for wireless network, which is a challenging task due to the mobility uncertainty of user. Motivated from a rationale, i.e., a good data compressor should be a good predictor, we proposed a mobility prediction algorithm. Integrating the prediction algorithm into GC, a resource allocation scheme is also proposed. The numerical simulation results show that the time-complexity of our proposed scheme is worse, but it outperforms *Fixed-percent* and *ExpectedMax* in the QoS support effectiveness.

1 Introduction

As known, the movement of the mobile users is greatly uncertain, which greatly impacts the efficiency of QoS schemes in wireless networks. In information theory, the Shannon entropy is a good method to quantitatively describe the uncertainty. In the same way, it can also scale the uncertainty of movement of mobile user. If the trajectory of movement of mobile user is regarded as a sequence of event, we can predict the next event by a certain data compression algorithm. Motivated by the theoretic bases and observations, this paper proposes a novel resource allocation and reservation scheme based on *Ziv-Lempel* algorithm, which is both theoretically optimal and good in practice.

2 The Description of the Model of User Mobility

Here, we use a generalized graph model to represent the actual wireless network (shown as Fig.1), where the cell shape and size may vary depending on many factors, such as the receiver sensitivity, the antenna radiation pattern of the base stations, and propagation environment, and the number of neighboring cells, which can be arbitrary but bounded and vary from cell to cell. An actual network can be represented by a bounded-degree, connected graph $G = (V, E)$, where the vertex-set V represents pairs of cells and the edge-set E represents the adjacency between pairs of cells. The example network shown in Fig. 1 can be modeled by the vertex set $V=\{a,b,c,d,e,f,g,h\}$ and the edge set $E=\{(a,d),(a,b),(b,c),\dots,(e,g)\}$.

In wireless networks, a call during its lifetime can be represented by a sequence of events $\{N H_1 H_2 S H_3 H_n S \dots E\}$, where N denotes the event that a new call is admitted, H_n denotes the event of a mobile user n th handoff, S denotes the event of the call sojourning in the same cell and E denotes the call termination event. Note that in some cases, there are no handoff events during the lifetime of a call and thus no H_n in the sequence of events. According to the representation of the call events sequence, the trajectory of movement of mobile user can be also easily represented by a sequence of cells $\{v\}$, where $v(\)$ denotes the cells users handoff to. In the example network shown in Fig. 1, the trajectory of movement of a certain mobile user may be the cells sequence $\{aabbchfdedfch\dots\}$. For a mobile user, its current location and the trend of movement can be described through these two sequences.

Fig. 1. Modeling an actual wireless cellular network

3 Mobility Predictions and Update Based on Data Compressor

For the mobility prediction processing, some literatures assume that the users independently handoff to its neighboring cells with equal probability, or assume that all of handoff events are independent and identically distributed. However, neither of them can exactly depict the mobility of users. Contrarily, the high-order Markov chain and the finite-context model are fairly reasonable. Of course, the order is higher, and the depictions of the actual movement can be more accurate, but the calculations of conditional probability and joint probability are also more difficult. Based on the definitions of entropy and conditional entropy in Ref. [6-7], the conditional entropy has a limit which equals to the per symbol entropy for a stationary stochastic process. So for each Markov chain and finite-context model, it is sure that there exists an appropriate order that depends on the mobility pattern. But its determination is a strenuous work, which root from the following factors. Firstly, its codeword is fixed-length because the conditional events of the N -order Markov chain are usually represented as $v_n | v_1 v_2 \dots v_{n-1}$, which is equivalent to N -symbol codeword. Secondly, the relationship in the context is simplex and independent, and does not vary with the input sequences. Hence, for the mobility prediction processing, only the model with variable-length codeword and adaptive-context is reasonable and practicable. According to the analyses of Ref. [2-3], the symbol-based version of the *Ziv-Lempel* algorithm can become the best candidate for the model because it is both theoretically optimal and good in practice.

Essentially, the *Ziv-Lempel* algorithm is universal variable-to-fixed coding scheme, which parses the input string S into block-to-variable distinct but the shortest substrings $\{s_1, s_2, s_3, \dots\}$ in a greedy manner. For each $j \geq 1$, substring s_j without its last character is equal to some previous substring s_i , where $j > i \geq 0$.

Example 1: Let the symbols be $\{a, b, c, d\}$, and given an input string $S = \{aaababbbbaabccddcbaaaa\dots\}$, then the *Ziv-Lempel* encoder can parse it into the substrings $\{a, aa, b, ab, bb, bba, abc, c, d, dc, ba, aaa, \dots\}$.

Fig. 2. The trie constructed in Example 1

The *Ziv-Lempel* coding process is interlaced with the learning process for the source characteristics. The key to the learning is a greedy decorrelating process, which implements by efficiently creating and looking up an explicit codeword dictionary. Because of the prefix property, substring parsed so far can be efficiently maintained in a trie [3], which can store statistics information for contexts explored besides representing the codeword dictionary. Fig. 2 shows the trie formed by Example 1. Through the trie, a new codeword can be easily created by concatenating a single symbol v to a parsed codeword s_i . As the parsing process progresses along with the string extending, larger and larger codeword accumulate in the dictionary. At the same time, the trie will be updated. Consequently, the estimates of conditional probabilities for larger contexts can be built up. Moreover, the learning capacity of the trie can be boosted up, and its prediction is also more precise.

The trajectory of movement of mobile user can be regarded as a substring in the symbol-based *Ziv-Lempel* algorithm. Similarly as shown in Fig. 3, we can also construct a mobility pattern predictor of the mobile user according to its mobility information base, which is equivalent to the trie. In natural, the predictor is a probability model based on *Ziv-Lempel* algorithm. When a new call is admitted, the predictor will set the current cell as a root of its mobility pattern, and update the probabilities of its possible events (including handoff and termination) during the call lifetime. When an event occurs in the sampling point, the predictor firstly judges whether it is the mobility pattern or not. If it is in the pattern, then the mobility pattern will be extended to the deeper layer, and be ready to the next prediction. Contrarily, a prediction fault is generated, and the mobility pattern and the context of current codeword are updated, as shown the red mark part in Fig. 3.

Fig. 3. The mobility prediction process of the symbol-based version of Ziv-Lempel encoder

The performance of the predictor can be evaluated by two metrics, i.e., the prediction fault rate and the expected fault rate. The former is defined as the ratio of the total number of prediction faults to the total number of events, and the latter is defined as the best possible fault rate achievable by any prediction algorithm which makes its prediction based only on the past mobility pattern history.

4 The Dynamic Resource Allocation and Reservation Scheme

Since forced call terminations due to handoff blocking are generally more objectionable than new call blocking, the handoff of a call should be treated in higher priority than the admission of new call, which is a default rule for service provider, and is also the premise of our scheme in this paper. To improve the QoS capacity of wireless networks, we must address the resource allocation and reservation scheme, which critical evaluating factors usually include handoff dropping probability, new call blocking probability, and the reserved resource utilization.

Among many schemes, the guard channels (GC) policy [1] and its revisions are simple, but they cannot satisfy the fluctuation of resource requirement due to user's mobility. However, their drawbacks can be overcome if their operations are based on the mobility predictor. So we can propose a scheme called prediction-based GC.

Before the prediction-based GC puts into effect, the most likely $cell_j$ (marked as MLC), which a mobile user may handoff to, must be firstly selected from the neighbor (marked as $Neighbor_Cell$) of current $Cell_i$ based on the mobility predictor in section

3. $Neighbor_Cell(Cell_j)$ can be obtained from the non-zero items in the adjacency matrix (1). Note that the two cell set meet the following relation:

$$Cell_j \in MLC(Cell_i) \subseteq Neighbor_Cell(Cell_i) \quad (1)$$

Then we can pertinently allocate and reserve resource in $MLC(Cell_i)$ for the call during its lifetime.

Fig. 4. The model of resource allocation and reservation during the call lifetime

As shown in Fig. 4, the call which handoffs to or originates from $Cell_i$ is our discussion objective. Assumed that the call comes from N_1 source neighbor cells, and possibly handoffs to N_2 target neighbor cells. There exist n_i and n_i calls in each source and target neighbor cells, respectively. According to the above mobility predictor, we can get the context (i.e., transition probability) of the handoff event from $Cell_j$ to $Cell_i$ (from $Cell_i$ to $Cell_{j'}$). The resource requirement in $Cell_i$ will fluctuate along with the calls continuously arrival at and departure from $Cell_i$, which is represented as follows:

$$\Delta BW(N1, N2) = \sum_{l=1}^{N1} P_{i,l} \cdot \sum_{k=1}^{n_l} BW_k - \sum_{l'=1}^{N2} P_{i,l'} \cdot \sum_{k=1}^{n_{l'}} BW_k \quad (2)$$

where BW_k denotes the effective-bandwidth [5].

When a new call arrives at $Cell_i$, which resource requirement is BW , its operation strategy is represented by the following expression:

$$Available_BW_of_Cell_i > BW + \Delta BW \quad (3)$$

If the expression (4) holds, then the scheme admits the call, or else rejects it.

When m calls handoff to $Cell_i$ while n calls terminate or handoff from $Cell_i$ to other cells, its strategy is represented by the following expression:

$$Available_BW_of_Cell_i > BW_{Reserved} \quad (4)$$

where $BW_{Reserved} = \Delta BW(N1+m, N2+n) - \Delta BW(N1, N2)$. If the expression (5) holds, then the scheme admits the calls handoffing to $Cell_i$, and reserves resources for them in advance, or else rejects the handoff requests.

5 Performance Analysis and Numerical Simulation

Our simulation network is a random Waxman-based network with 100 nodes (i.e., 100 cells). For simple, assumed the call creates in Poisson random process with average arrival rate λ and holding-time μ^{-1} , the total resource of each cell is 100 unit, and the resource requirement of each call uniformly distributes in the range [1, 20] unit. During the call lifetime, the trajectory of movement of mobile user is represented by the trace of a sub-graph of 100-node Waxman network.

Fig. 5. The QoS performance of our proposed scheme compared with other schemes

Here, we evaluate our proposed scheme by the comparison with *Fixed-percent* and *ExpectedMax* [4] from two aspects, i.e., the time-complexity, and the QoS performance which is depicted by the handoff dropping probability P_{hd} , the new call blocking probability P_{nb} , the reserved resource utilization, and the overall call blocking probability. For *Fixed-percent*, assumed that the reserved resource for handoff occupies 8% of total resource in each cell.

Fig.5(a) and (b) illustrates the performances of three schemes in the handoff dropping and the new call blocking. As expected, P_{hd} and P_{nb} for the three schemes increase with the call arrival rate. But, both of P_{hd} and P_{nb} in our proposed scheme is the lowest, which benefits from the mobility prediction. Our proposed scheme considers the mobility of user during the resource reservation, and the reservation operations just aim at the predicted cells, i.e., $MLC(Cell_i)$. Obviously, the resource waste due to

the useless reservations in each cell is reduced. Therefore, P_{hd} and P_{nb} can be improved.

The reserved resource utilization is illustrated in Fig.5(c). When $\lambda < 3.5$, it will rise sharply. But when $\lambda > 3.5$, their distinctions will be more and more evident. In *Fixed-percent*, the reserved resource utilization will slowly rise and approach its limit 100%. Contrarily in *Predict-based* and *ExpectedMax*, it will slightly decrease instead. It can be explained as follows. When λ increases, the constant resource reserved exclusively for the handoff process would be depleted, and cannot suffice the process of more handoff events. Hence, the utilization rate of its reserved resource certainly reaches 100%. *Predict-based* and *ExpectedMax* reserve resource based on the mobility prediction. Moreover, these schemes exist some unavoidable prediction faults, which will appear frequently, and so incur much more invalid reservation operations when λ increases. Hence, it is impossible for *Predict-based* and *ExpectedMax* that the utilization rate is as high as *Fixed-percent*. As a whole, the utilization rate of *Predict-based* is better than that of *ExpectedMax* When λ is high. The advantage comes from the better accuracy of mobility prediction based on Ziv-Lempel algorithm in *Predict-based*.

Obtained from the results in Ref. [8], the estimate of the overall call blocking probability in $Cell_i$ can be expressed as follows

$$P(\text{Load}_{Cell_i} \geq C) \leq \left(\frac{\text{Load}_{Cell_i}}{C} \right)^C \cdot e^{-\text{Load}_{Cell_i}} \quad (5)$$

where Load consists of the actual resource used by the existing calls in $Cell_i$, and the reserved resource in $Cell_i$ for some arriving calls. In the comparison of Fig. 6, we take the upper bound. As illustrated by Fig. 5, when $\lambda > 3.5$, our proposed scheme distinctly outperforms *Fixed-percent* and *ExpectedMax*. Generally, the call arrival rate is more than 3.5-call/second in actual wireless network. The result in Fig. 5 (d) shows that it is significant for our proposed scheme to improve the overall call blocking.

Fig. 6. The comparison of processing time, which of *Predict-based* acts as benchmark

As a whole, our proposed scheme will incur overhead as other schemes with mobility prediction. Here, we evaluate the overhead in terms of time-complexity. As shown by Fig. 6, the relative time-complexities of *Fixed-percent* and *ExpectedMax* are better than that of our proposed scheme. But when $\lambda > 3.5$, the distinction between *Predict-based* and *ExpectedMax* will be more and more blurring.

6 Conclusions

Due to the mobility uncertainty of mobile user, it is a real challenge for wireless network to efficiently allocate and reserve resource. Firstly motivated from a rationale, i.e., a good data compressor should be a good predictor, this paper develops a mobility prediction algorithm based on the Ziv-Lempel algorithm, which is both theoretically optimal and good in practice. Theoretically, the prediction algorithm can predict not only to which cell a mobile user will handoff but also when the handoff will occur. Then, we propose an efficient re-source allocation and reservation scheme, called predict-based GC, which integrates the prediction algorithm into the guard channels (GC) policy. The simulation results show that the time-complexity of our proposed scheme (i.e., predict-based GC) is worse, but it outperforms Fixed-percent and ExpectedMax in the QoS support effectiveness.

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